## Problem 1

To enforce the necessary constraints, we introduce the Lagrangian multipliers  $\lambda_1, ..., \lambda_M, \lambda_{M+1}$  and make an unconstrained maximization of

$$L = \mathbf{u}_{M+1}^{\mathsf{T}} \mathbf{S} \mathbf{u}_{M+1} + \lambda_{M+1} (1 - \mathbf{u}_{M+1}^{\mathsf{T}} \mathbf{u}_{M+1}) + \sum_{i=1}^{M} \lambda_i (\mathbf{u}_{M+1}^{\mathsf{T}} \mathbf{u}_i)$$

Now we take the derivative of L with respect to a vector  $\mathbf{u}_{M+1}$  and set it to zero

$$\frac{\partial}{\partial \mathbf{u}_{M+1}} L = 0 \Leftrightarrow 2\mathbf{S} \mathbf{u}_{M+1} = 2\lambda_{M+1} \mathbf{u}_{M+1} - \sum_{i=1}^{M} \lambda_{i} \mathbf{u}_{i}$$

$$\Leftrightarrow 2\mathbf{u}_{M+1}^{\mathsf{T}} \mathbf{S} \mathbf{u}_{M+1} = 2\lambda_{M+1} \mathbf{u}_{M+1}^{\mathsf{T}} \mathbf{u}_{M+1} - \sum_{i=1}^{M} \lambda_{i} \mathbf{u}_{M+1}^{\mathsf{T}} \mathbf{u}_{i} \qquad \text{(left-multiply by } \mathbf{u}_{M+1}^{\mathsf{T}}\text{)}$$

$$\Leftrightarrow \mathbf{u}_{M+1}^{\mathsf{T}} \mathbf{S} \mathbf{u}_{M+1} = \lambda_{M+1} \qquad \text{(by orthonormality of } u_{i} \text{ and } \mathbf{u}_{M+1}\text{)}$$

By induction step, we see that the variance in direction  $\mathbf{u}_{M+1}$  is maximum when we set  $\mathbf{u}_{M+1}$  equal to the eigenvector having the  $(m+1)^{\text{th}}$  largest eigenvalue  $\lambda_{M+1}$ .

## Problem 2

$$\mathbf{x_i} \sim \mathcal{N}(\mu_{\mathbf{x}}, \mathbf{\Phi_{\mathbf{x}}})$$
  $(\mu_{\mathbf{x}} = \mu, \mathbf{\Phi_{\mathbf{x}}} = \mathbf{W}\mathbf{W}^{\intercal} + \Phi^2 \mathbf{I})$ 

From lecture we know that  $\mathbf{y_i} = \mathbf{A}\mathbf{x_i} \sim \mathcal{N}(\mu_y, \Phi_y)$ . Let's first derive the two moments

$$\begin{split} \boldsymbol{\mu}_{\mathbf{y}} &= \mathbf{E}[y] \\ &= \mathbf{E}[\mathbf{A}\mathbf{x}] \\ &= \mathbf{A}\mathbf{E}[\mathbf{x}] \\ &= \mathbf{A}\boldsymbol{\mu}_{\mathbf{x}} \end{split}$$

$$\begin{split} \boldsymbol{\Phi}_{\mathbf{y}} &= \mathbf{E}[(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}})(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}})^{\intercal}] \\ &= \mathbf{E}[(\mathbf{A}\mathbf{x} - \mathbf{A}\boldsymbol{\mu}_{\mathbf{x}})(\mathbf{A}\mathbf{x} - \mathbf{A}\boldsymbol{\mu}_{\mathbf{x}})^{\intercal}] \\ &= \mathbf{E}[(\mathbf{A}(\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}}))(\mathbf{A}(\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}}))^{\intercal}] \\ &= \mathbf{A}\mathbf{E}[(\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}})(\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}})^{\intercal}]\mathbf{A}^{\intercal} \\ &= \mathbf{A}\boldsymbol{\Phi}_{\mathbf{x}}\mathbf{A}^{\intercal} \end{split}$$

By pattern matching we have for the transformed Maximum Likelihood estimates

$$egin{aligned} \mu_{y_{ML}} &= \mathbf{A} \mu_{ML} \ \mathbf{\Phi}_{y_{ML}} &= \mathbf{A} \mathbf{\Phi}_{ML} \mathbf{A}^\intercal \ \mathbf{W}_{y_{ML}} &= \mathbf{A} \mathbf{W}_{ML} \end{aligned}$$

By orthogonality  $\mathbf{A}\mathbf{A}^{\intercal} = \mathbf{A}^{\intercal}\mathbf{A} = \mathbf{I}$  and  $\mathbf{\Phi} = \sigma^2\mathbf{I}$  we have

$$\mathbf{A}\mathbf{\Phi}\mathbf{A}^{\mathsf{T}} = \mathbf{A}\sigma^{2}\mathbf{I}\mathbf{A}^{\mathsf{T}}$$
$$= \sigma^{2}\mathbf{A}\mathbf{A}^{\mathsf{T}}$$
$$= \sigma^{2}\mathbf{I}$$

## Problem 3

Let  $\mathbf{x} \in \mathbb{R}^5$  hold the movie ratings given by Leslie. By the SVD projection in concept space we have

$$\mathbf{V} \cdot \mathbf{x} = [1.74, 2.84]^{\mathsf{T}}$$

By SVD decomposition and reconstruction of the input using the projected space we have

$$[1.74, 2.84]^{\mathsf{T}} \cdot \mathbf{V}^{\mathsf{T}} = [1.0092, 1.0092, 1.0092, 2.0164, 2.0164]^{\mathsf{T}}$$

E.g. we can predict that Leslie will rate Titanic movie with 2.0164.

## Problem 4

See below.